

**VITAL ASPECT OF RESPIRATION AND CHANGE IN BRAIN SIGNAL DURING
MEDITATION USING EEG AND MACHINE LEARNING**

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Abstract

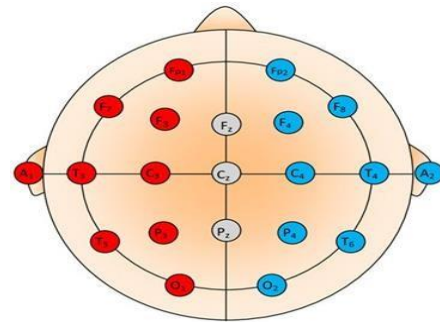
Practicing breathing can enhance an individual's antioxidant status in addition to helping them cope with life's pressures. An increase in antioxidant status is useful in reducing many free radicals that are formed when the food is processed by our body or when we are constantly around things like pollution, smoke, etc. Due to the less oxidation states in the body, the practitioner gets a boost in the immune system with less vulnerability to disease causing microbes [2]. A change of EEG and respiration signals that are rewarded after breathing exercises (e.g. Kriya Yoga), show the qualitative change in human life. After a specific week of meditation, EEG and breathing data were gathered and evaluated on a number of inexperienced mediators, former yoga practitioners, and monks. Spectral analysis, phase analysis, and classification were used to assess the objective marker for meditation [6]. In order to determine if breathing feature vectors and EEG data are reliable objective markers of meditation skill, this research article will incorporate methods employed in machine learning, comprising Decision Trees, Support Vector Machines(SVM), and Random Forest classifiers. This study examines the mindfulness meditation measure (mm), a mental exercise that allows one to sustain a state of relaxation.

Keywords: support vector machine, EEG, MM.

1. Introduction

Our breathing rhythm and patterns are influenced by our thoughts and feelings. There is a breath- emotion loop since our emotional and mental states are intimately correlated with our breathing. Consciously slowing down and deepening our breathing causes our mind to instantly become relaxed and at ease. Our mental and emotional states can be reclaimed in a matter of minutes. We can think of Diaphragmatic breathing as offering a massage to our internal organs and glands. Calm, deep belly breathing can also boost immunity by altering the gene expression of specific immune cells, according to a Public Library of Science study based on yoga breath exercises. (1)

A lateral view of the human brain with color-coded lobes and labeled anatomical features. The Frontal lobe is yellow, the Parietal lobe is blue, the Temporal lobe is green, and the Occipital lobe is orange. The Central sulcus separates the frontal and parietal lobes. The Parieto-occipital sulcus separates the parietal and occipital lobes. The Preoccipital notch is located on the occipital lobe. The Lateral fissure separates the temporal lobe from the frontal and parietal lobes. The Frontal pole is at the anterior tip of the frontal lobe, and the Temporal pole is at the anterior tip of the temporal lobe.



2. Related Works

Year	Number of training data	Number of channels	Type of stress	Experiment Duration	Frequency bands	Features	Classifier	Notes
2021	5	32	Mental Arithmetic	40 mins	Theta, Alpha, Beta	6 statistical feature, PSD, HOC, HJORTH PARAMETERS ,FRONTAL ASYMMETRIC ALPHA	SVM	GA based method out performed in detections of accuracy
2020	5	30	TSST	40 MINS	Delta, Theta, Alpha, Beta	Transitivity, modularity ,path length	SVM	Salivary cortisol level increase during TSST, classifier arrives with alpha and beta bandwidth
2020	5	30	Conscious breathing and meditation	45 mins	Gamma, High Beta, High Alpha	Relative change in amplitude and frequency	SVM	Remarkable change in brain signal during meditation
2022	7	4	mist	24 min	1-4 Hz, 4-7 Hz, 8-13 Hz, 14-30 Hz, 30-45 Hz	Delta , Theta, Alpha, Beta, Gamma	<u>SVM</u>	Comparison between stress

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year and

examinations of the student during COVID pandemic in year 2019.

3.5. Elimination Criteria:

Students practicing yoga sincerely and students who regularly engages their muscles through any kind of physical exercises are debarred from this research.

3.6. Materials used

- Oximeter
- Earphones
- Weighing machine
- Non-invasive automatic blood pressure monitor
- EEG
- Pre-designed Questionnaire

In order to determine the classification of mental stress, the stress study has looked at a variety of classifiers (2). The common and significant classifiers are Support vector machine (SVM), Decision Tree classifier, Random Forest classifier. The Hypothalamus Pituitary Adrenocortical Axis (HPA) and Sympathetic Nervous System (SNS) regulate humans' physiological responses (3). Before using that analysis method, the EEG data is subjected to a series of rigorous preprocessing steps to eliminate noise and artifacts.

EEG Report -

	A	B	C	D	E
	SUBJECTS (STUDENTS AGE(18-26)	TIME	BEFORE (KRIYA PRANAYAM) HIGH RANGE BETA SIGNAL	DURING (KRIYA PRANAYAM) BETA & ALPHA	AFTER (KRIYA PRANAYAM) ALPHA
2					
3	SUBJECT-1	1MIN	29	17	9
4		3MIN	33	18	12
5		5MIN	34	17	9
6		7MIN	13	17	8
7		10MIN	20	17	9
8	SUBJECT-2	1MIN	29	18	8
9		3MIN	30	13	9
10		5MIN	29	14	9
11		7MIN	12	13	12
12		10MIN	26	16	9
13	SUBJECT-3	1MIN	21	18	10
14		3MIN	32	13	8
15		5MIN	29	18	12
16		7MIN	23	12	8
17		10MIN	29	14	9
18	SUBJECT-4	1MIN	25	18	9
19		3MIN	14	16	12
20		5MIN	16	12	11
21		7MIN	15	16	12
22		10MIN	26	16	10
23	SUBJECT-5	1MIN	26	15	11
24		3MIN	25	13	8
25		5MIN	31	12	11
26		7MIN	27	18	12

A	B	C	D	E
SUBJECTS (STUDENTS AGE(16-26))	TIME	BEFORE (KRIYA PRANAYAM) LOW RANGE BETA SIGNAL	DURING (KRIYA PRANAYAM) ALPHA	AFTER (KRIYA PRANAYAM) LOW RANGE ALPHA
SUBJECT-1	1MIN	15	9	9
	3MIN	14	9	10
	5MIN	14	12	10
	7MIN	13	10	10
	10MIN	15	8	10
SUBJECT-2	1MIN	15	10	10
	3MIN	15	8	9
	5MIN	12	10	10
	7MIN	12	11	10
	10MIN	14	10	10
SUBJECT-3	1MIN	15	10	9
	3MIN	12	12	10
	5MIN	12	8	10
	7MIN	13	12	10
	10MIN	13	11	8
SUBJECT-4	1MIN	12	11	10
	3MIN	12	11	9
	5MIN	14	8	9
	7MIN	14	8	9
	10MIN	14	8	10
SUBJECT-5	1MIN	12	12	9
	3MIN	14	11	9
	5MIN	15	8	8
	7MIN	13	10	9

A	B	C	D	E
BRAIN WAVE SIGNALS THROUGH EEG (IN HZ)				
SUBJECTS (MONKS AGE(22-60))	TIME	BEFORE (KRIYA PRANAYAM) ALPHA	DURING (KRIYA PRANAYAM) THETA	AFTER (KRIYA PRANAYAM) THETA & DELTA
MONK-1	1MIN	12	4	2
	3MIN	8	7	3
	5MIN	10	8	2
	7MIN	12	7	2
	10MIN	12	8	2
MONK-2	1MIN	11	4	4
	3MIN	10	8	2
	5MIN	12	8	3
	7MIN	10	8	3
	10MIN	9	8	2
MONK-3	1MIN	11	7	3
	3MIN	11	7	4
	5MIN	12	5	2
	7MIN	9	7	3
	10MIN	8	7	2
MONK-4	1MIN	11	7	2
	3MIN	8	7	4
	5MIN	9	4	2
	7MIN	12	7	3
	10MIN	9	5	2
MONK-5	1MIN	12	5	2
	3MIN	8	4	3
	5MIN	12	4	3

The most frequent physiological aberrations that affect the EEG signal include eye blinks, head and body movements, electrolyte concentration changes at electrodes and DC offset,

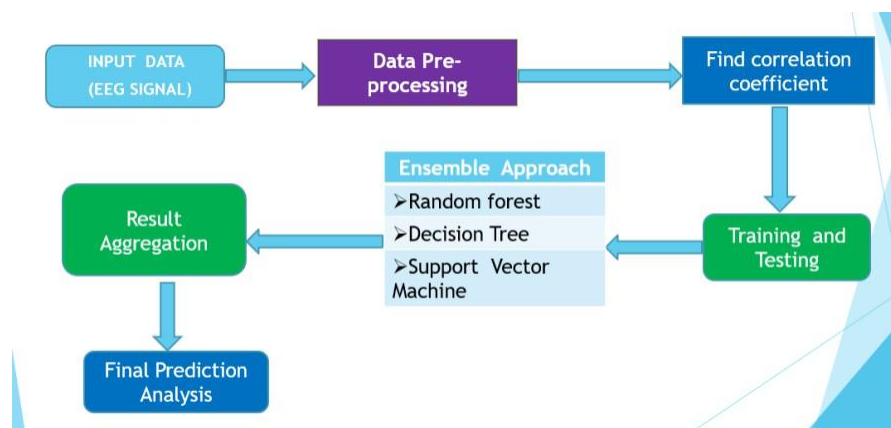
sambhavamudra practice, and mindful breathing.

4. Key observations

The heart's beating rate was significantly lowered by mindful breathing, which was followed by regular inhalations and exhalations. This reduced stress brought on by anxiety. Remarkably, the effects of suppressing some types of emotions influence our body metabolisms, leading to elevated blood

pressure and heart rate. For example, in a group of students debating among themselves to prove their theories are true, the student who participated the least was found to be most stressed out due to anxiety, which was caused by suppressing expression. A reduction in breathing rate and a subsequent drop in blood pressure were the results of synchronizing aerobics or any physical exercise with the regulated breathing pattern that is widely recognized as "ASANAS."

4.1 Proposed Model



EEG Signal Analysis



Figure 4.1.1:

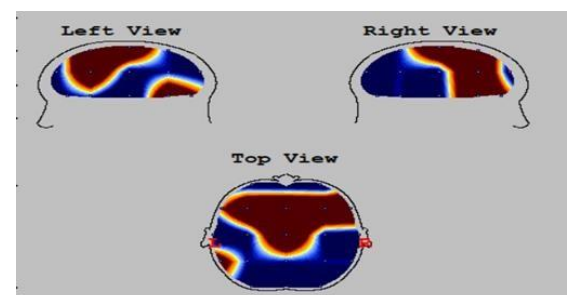


Figure 4.1.2:

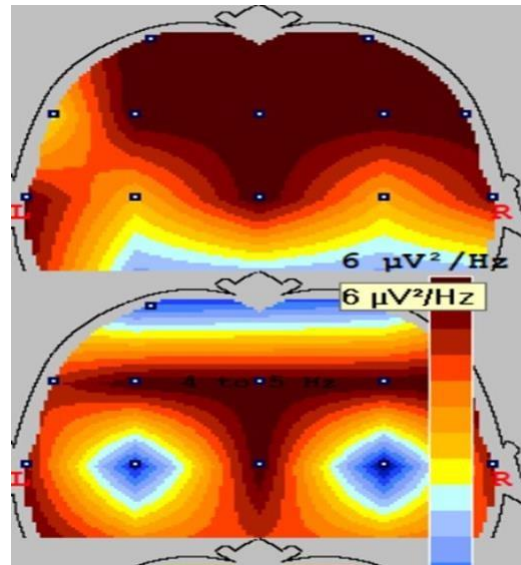


Figure 4.1.3:

4.2. Data Processing

Data cleaning and transformation processes, which is a subset of data readiness process, involves performing various operations on unprocessed data to prepare it for further task in handling data (4). It has always been a preliminary stage in the procedure of data mining. It describes preparing data for analysis by cleaning, converting, and integrating it. (3). Data preparation aims to enhance data quality and tailor the data to the specific requirements of the intended data mining task.

	X_train	mean_0_a	mean_1_a	mean_2_a	...	fft_747_b	fft_748_b	fft_749_b
1	28.800	33.10	32.0	-31.60	-31.60	2.570		
6	10.800	21.00	44.7	-55.20	-55.20	40.600		
27	6.220	17.80	25.1	26.70	26.70	18.500		
49	16.800	19.90	-288.0	-271.00	-271.00	552.000		
24	4.560	30.00	23.8	-132.00	-132.00	-69.700		
31	1.580	26.70	27.8	-49.00	-49.00	45.200		
15	12.700	23.80	-193.0	-161.00	-161.00	427.000		
35	22.800	32.60	-136.0	-35.30	-35.30	41.900		
26	28.300	30.10	29.0	-19.20	-19.20	-5.600		
7	17.800	27.00	-162.0	-186.00	-186.00	384.000		
20	10.300	33.20	-217.0	-29.80	-29.80	-28.400		
48	-0.547	28.30	-259.0	-10.50	-10.50	-169.000		
3	14.900	31.60	-143.0	9.53	9.53	-12.400		
23	8.530	25.40	-295.0	-17.00	-17.00	61.200		
44	27.500	29.10	25.3	-48.80	-48.80	7.040		
4	28.300	31.30	45.2	23.90	23.90	-17.600		
16	0.425	34.90	53.9	-61.50	-61.50	-21.200		
36	29.100	32.20	25.3	-8.26	-8.26	-0.580		
14	28.800	31.80	30.1	4.93	4.93	-17.300		
43	6.160	18.90	-245.0	32.70	32.70	-98.900		
25	15.400	30.30	-61.5	-161.00	-161.00	431.000		
37	27.400	30.40	28.3	3.08	3.08	-0.548		
39	16.000	33.80	-132.0	7.62	7.62	16.700		

Figure 4.2.1:

4.3. Testing the dataset

Independent test data, distinct from the dataset used for training, evaluating a machine learning model's generalization performance relies heavily on the training dataset of a trained model. This test set provides an unbiased analyzing the accuracy of a model's predicted outcomes on unseen instances, thereby demonstrating the success of the training phase and the model's ability to perform on unseen data. While the test set should ideally remain unchanged during the final evaluation to maintain objectivity, iterative model refinement may involve using validation sets (subsets of the training data) to guide hyper-parameter tuning and model selection.

There are two primary criteria for testing data: It should:

- Authentically depict the dataset.
- Have enough size to produce accurate forecast.

TIME	BEFORE (KRIYA PRANYAM)	... AFTER (KRIYA PRANYAM)	Label
0	1	11 ...	9 1
1	3	11 ...	10 0
2	5	11 ...	9 0
3	7	10 ...	5 1
4	10	11 ...	7 0

Figure 4.3.1:

4.4. Classification Algorithms

4.4.1. Support Vector Machine (SVM)

The fundamental objective of an SVM classifier aims to identify the best possible decision boundary, that effectively separates data belonging to Kriya Yoga practitioners, non-practitioners, and monks,

enabling efficient future classification. In this case each table consists of three individual columns which possess data regarding the signals, (alpha, theta and delta) emitted from our brain before, after and during the kriya pranayama. And through this analysis we came to conclusion that pranayama acts as a crucial factor in our respiration and respiration control these signal emissions.

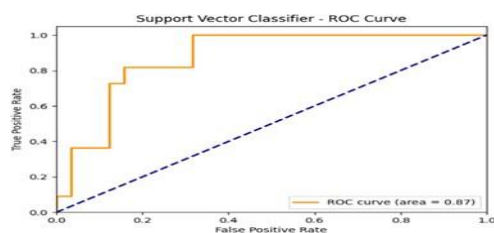


Figure 4.4.1 :

4.4.2. Random Forest Classifier

4.4.3.

A Random Forest classifier employs an ensemble of decision trees for prediction. Each tree independently determines a class, and the final classification is reached through a majority vote among the trees.

This algorithm has the lowest accuracy of 85 percentage.

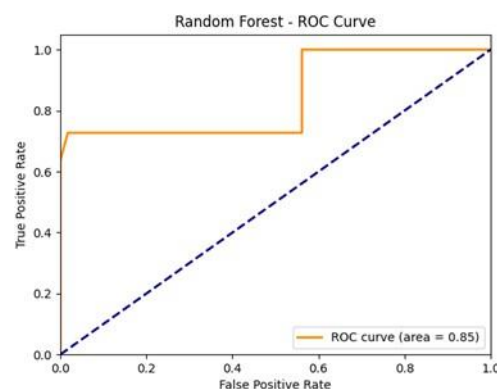


Figure 4.4.2 :

4.4.4. Decision Tree Algorithm

Although it may be applied to both classification and regression problems, decision trees are a super

-vised learning technique that are most often employed to solve classification difficulties (5). In a decision-tree classifier, dataset features are used to define internal nodes, which are connected by branches representing decision rules that ultimately lead to leaf nodes representing the final classification.

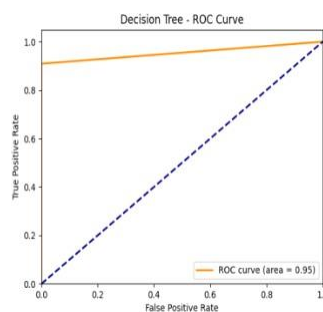


Figure 4.4.3 :

In correlation matrix we calculate the interdependence of each attributes with other attributes including itself. This provides a temperature scale in which a cooler colour represents less

dependency and warmer colour represents more dependency.

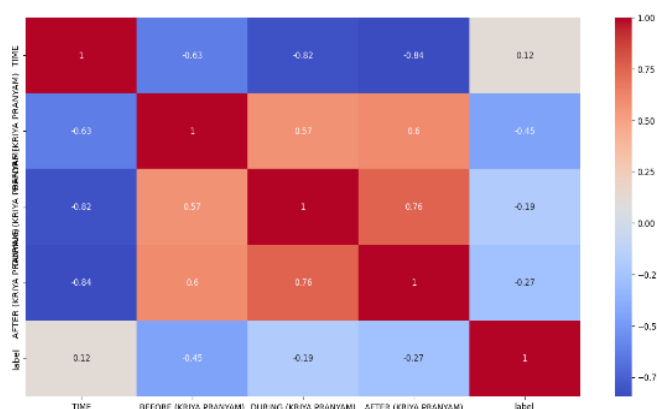
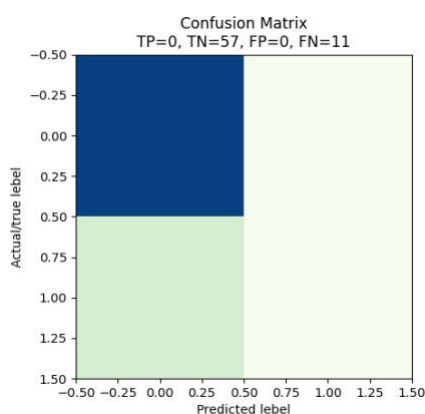


Figure 4.4.4 :

4.5. Confusion Matrix

A confusion matrix is used to evaluate the performance of a classification model by examining four distinct scenarios based on actual versus predicted outcomes:

1. **True Positive (TP):** This indicates that the model has accurately predicted a positive outcome.
2. **True Negative (TN):** This signifies that the model has correctly identified a negative outcome.
3. **False Positive (FP):** This occurs when the model incorrectly predicts a positive result, although the actual outcome is negative.
4. **False Negative (FN):** This happens when the model wrongly predicts a negative result, even though the actual outcome is positive.



$$\begin{aligned}
 \text{precision} &= \frac{TP}{TP + FP} \\
 \text{recall} &= \frac{TP}{TP + FN} \\
 F1 &= \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \\
 \text{accuracy} &= \frac{TP + TN}{TP + FN + TN + FP}
 \end{aligned}$$

Figure 4.5.1:

In the provided sample the best algorithm is random forest to use in confusion matrix as it has highest accuracy and precision.

	accuracy	F1-score	Recall	precision
Random Forest	86.66	86.59	87.77	86.67
Logistic Regression	33.33	16.66	33.34	33.34
Support Vector Machine	80.00	79.54	81.11	80.00

5. Conclusion

Research work is to analyze the EEG signal during various activities and the temporal change in brain which continues practice of meditation. It results a permanent change in volume and density of hippocampus and amygdala, and activate the frontal context of human brain through EEG.

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